Retrieval of soil moisture from AMSR data

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Abstract—In this paper we discuss the potential and problems of soil moisture sensing using AMSR data that will become available in late 2000 or early 2001. The Advanced Microwave Scanning Radiometer (AMSR) will be the first spaceborne radiometer since the Nimbus-7 SMMR to include a frequency at C-band (6.9 GHz). The ability to penetrate vegetation, and to sense deeper in the soil, increases with wavelength. The AMSR is thus expected to have a better soil moisture sensing capability than the DMSP SSM/I or TRMM Microwave Imager (TMI) instruments which have lowest frequencies of 19.35 and 10.7 GHz, respectively. The spatial resolution of the AMSR at 6.9 GHz is approximately 60 km, a factor of two better than the SMMR. While not optimal for soil moisture sensing, the AMSR should provide useful information over low-vegetated areas, and will serve as a valuable precursor to future proposed L-band soil moisture sensors. Vegetation and snow cover, frozen ground, topography, open water, and footprint heterogeneity are factors that must be considered in estimating soil moisture. Thus, ancillary data that can provide information on surface characteristics will be useful in improving the retrievals. Descriptions and preliminary tests of different soil moisture retrieval approaches are discussed here. Experiments using surface measurements, airborne sensors, and satellite data are planned for continued development of the retrieval algorithms, and for validation of the derived soil moisture products after launch.

1. INTRODUCTION

The Advanced Microwave Scanning Radiometer (AMSR) will provide new data of interest for land surface studies, particularly for soil moisture sensing. The AMSR is currently planned for launch on the ADEOS-II and EOS PM-1 satellites in late 2000. The AMSR will operate with vertical and horizontal polarizations at frequencies of 6.9, 10.7, 18.7, 23.8, 36.5, and 89 GHz. It will be the first spaceborne radiometer since the SMMR in 1987 to include a C-band (~7 GHz) frequency. The TRMM Microwave Imager (TMI), launched in 1998, includes an X-band (10.7 GHz) frequency, but coverage is limited to the tropics (between ±~35° latitude). Penetration of vegetation and soil is greater at lower frequencies, thus the AMSR is expected to have better soil moisture sensing capability than either the SSM/I (with a lowest frequency of 19.35 GHz) or the TMI. The spatial resolution of the AMSR (~60 km) will be about a factor of two better than the SMMR, and is comparable to the grid scales of current climate models. While not optimal for soil moisture sensing, the AMSR should provide useful soil moisture information over low-vegetated areas, and will serve as a valuable precursor to future proposed L-band soil moisture sensors. The ADEOS-II and EOS PM-1 satellites will have equator crossing times of 10:30 am and 1:30 pm, respectively. By combining data from the AMSR instruments on both satellites an evaluation can be done of the improvement in soil moisture estimation obtainable by sampling at different points in the diurnal surface temperature cycle.

There are significant challenges to be overcome in developing algorithms for AMSR soil moisture sensing. Validation of the derived soil moisture products will also pose many problems. Vegetation and snow cover, frozen ground, topography, open water, and sub-footprint heterogeneity need to be considered in the retrievals. Extrapolation of the retrieved surface moisture to deeper soil layers is desired for some hydrologic applications. Registration of the AMSR data to an earth-fixed grid will be advantageous in using ancillary data sets, such as soil texture, topography, vegetation index, and climate data, to address some of these problems.

Approaches currently being developed for AMSR soil moisture retrieval are described in this paper. Since soil moisture is not currently measured from space, and is considered a challenging measurement, a number of different algorithms are being considered. Evaluation of these approaches is expected to extend through the post-launch validation phases. Experiments using in-situ surface measurements, airborne sensors, and satellite data are planned for further development of the retrieval algorithms, and for validation of the derived products after launch. The ADEOS-II and EOS AMSR validation activities will be conducted in conjunction with ongoing agency investigations in hydrometeorology and climate, and will include field experiments and data acquisitions planned by international programs such as the GEWEX Coordinated Enhanced Observing Period (CEOP) experiments.

2. MODELING

The research framework for soil moisture sensing using passive microwaves has been well established [1], [2], and includes an extensive history of field experiments and modeling studies. Most of these investigations have been performed at 1.4 GHz (L-band), with fewer studies done at the higher AMSR frequencies (C- and X-band). Algorithms for retrieving soil moisture from AMSR data require microwave models valid at the frequencies, viewing angle, and spatial resolution of the AMSR measurements. The models need to be relatively simple for satellite application yet physically meaningful. Some model parameters need to be estimated using ancillary data or other a-priori information.

The emission model most appropriate for AMSR soil moisture retrieval represents the land surface as a homogeneous, single-scattering vegetation layer above the soil. This model has been discussed by many authors [3], [4]. The soil is characterized by a surface reflectivity (r_p) and effective temperature (T_s). The reflectivity is related to the soil moisture (m_v) by the Fresnel expressions, modified for surface roughness. The vegetation acts as an attenuating and emitting layer, and is characterized by the opacity (τ_c), temperature (T_c), and single-scattering albedo (ω). The observed brightness temperature (T_{b_p}) is then given by

$$T_{b_p} = T_s\,[1 - r_p]\,\exp(-\tau_c) + T_c\,(1 - \omega)\,[1 - \exp(-\tau_c)]\,[1 + r_p \exp(-\tau_c)] \qquad (1)$$

where p refers to either vertical or horizontal polarization. The vegetation opacity is related to the vegetation water content, and less directly to the leaf area index. The single-scattering albedo is small, and is usually neglected, but can be estimated if necessary as a calibration parameter. The effects of atmospheric absorption and emission are not usually significant at frequencies of X-band and below.

Equation (1) represents the dominant physical mechanisms for surface emission and scattering but keeps to a minimum the number of free parameters that must be known or estimated. The following factors must be considered in applying the model since they affect the retrieval accuracy. First, the single scattering albedo and vegetation opacity can exhibit polarization dependence related to the orientations of leaves, stalks, and branches within the vegetation volume. Second, the effect of surface roughness on soil reflectivity is difficult to parameterize since few studies have been made of surface roughness at the AMSR footprint scale. Finally, since land surfaces are heterogeneous, the modeled and retrieved parameters must be interpreted as averages over the horizontal footprint and the vertical sensing depth [5]. At ~7–10 GHz the AMSR footprint is ~60 km, and the soil moisture sensing depth is on the order of less than a centimeter.

The most important relationship for soil moisture sensing is that between the soil dielectric constant (hence emissivity and reflectivity) and the soil volumetric moisture [6], [7]. This relationship is influenced by soil texture (represented by the fractional contents of sand, silt, and clay), and surface roughness. Ancillary data on soil texture and topography are thus useful in improving the accuracy of the retrievals.

The dependence of vegetation opacity on columnar water content (w_c) and leaf area index (LAI) has been studied both theoretically and experimentally. Two expressions developed independently to represent these relationships are [8], [9]

$$\tau_c = b\, w_c / \cos\theta \qquad (2)$$

$$\tau_c = [\,(k/\sqrt{\lambda})\ \ln(1 + w_c)\,] / \cos\theta = [\,(k/y\sqrt{\lambda})\ LAI\,] / \cos\theta \qquad (3)$$

where the $\cos\theta$ factor accounts for the slant observation path through the vegetation.

In the first expression, b is a parameter that depends on vegetation type and is approximately proportional to frequency. As frequency increases, the frequency dependence of b decreases, and its dependence on canopy structure increases [10], [11]. Thus, ancillary data on vegetation type or classification are useful to calibrate b for global applications. In the second expression, a logarithmic function is used to express the dependence of vegetation opacity on water content, and a linear dependence is used to relate the opacity to leaf area index. The coefficients k and y depend on vegetation characteristics and must be determined experimentally. Again, ancillary data are useful.

Variability in land surface temperature causes uncertainty in retrieving soil moisture. One method to compensate for this is to use ancillary information from meteorological surface air temperature data, or forecast model skin-surface temperatures. Another option is to use multichannel brightness temperature indices in the retrieval algorithm which are, to first order, independent of surface temperature. Indices of interest include a spectral gradient index (I_{sw}), and a polarization index (PI), which can be defined as

$$I_{sw} = \frac{(T_{b_i} - T_{b_j})}{\frac{1}{2}(T_{b_i} + T_{b_j})} \tag{4}$$

$$PI = \frac{(T_{b_v} - T_{b_h})}{\frac{1}{2}(T_{b_v} + T_{b_h})} \tag{5}$$

where I_{sw} is defined for a specific polarization, and for frequency *i* greater than *j*, and *PI* is defined for a specific frequency. The different sensitivities of these indices to soil moisture and vegetation can be exploited in the retrievals. For instance, lower frequencies penetrate deeper through vegetation and soil, are less sensitive to surface roughness, and are more sensitive to soil moisture. Hence, I_{sw} typically increases with soil moisture. Similarly, *PI* typically increases with soil moisture since the brightness temperature at horizontal polarization is more sensitive to soil moisture than at vertical polarization. *PI* also decreases with increasing vegetation and roughness, and is less sensitive to soil moisture at higher frequencies [9], [12].

3. ANCILLARY DATA

Ancillary data are useful for improving the accuracy of soil moisture retrievals, and are critical for some approaches. Much of the required data are readily available, but from diverse sources and in varying formats and resolutions. These data sets must be quality-controlled and registered to the satellite data. Some of the required data are static, such as soil texture and topography, while others vary in time, such as vegetation cover and surface temperature. The data must be used carefully, since in most cases the data parameters do not correspond directly to parameters of the microwave models. For instance, vegetation index (NDVI) is related indirectly to vegetation water content and leaf area index, while in-situ surface air temperature, and forecast model skin temperature, are related indirectly to the microwave-observed land surface temperature. Table 1 lists some of the candidate ancillary data sets and their sources.

4. RETRIEVAL ALGORITHMS

The AMSR C-band (6.9 GHz) horizontally polarized channel will be the most sensitive to soil moisture. An algorithm using this channel alone can be used to retrieve soil moisture if ancillary data are available to correct for surface temperature, vegetation, surface roughness, and soil texture. An algorithm of this form has been applied to soil moisture estimation using L-band (1.4 GHz) aircraft data [13].

By using normalized indices as defined in Equations (4) and (5), the reliance on ancillary surface temperature data can be avoided. One method is to use the indices *PI* and I_{sw}, at appropriate frequencies to estimate the vegetation correction and soil moisture. The two indices are chosen using frequencies that provide different sensitivities to soil moisture and vegetation, so that they can be used to retrieve these parameters independently. Alternatively, two *PI* indices at different frequencies, e.g. 6.9 and 10.7 GHz, can be used to estimate the vegetation correction and soil moisture. To implement

Table 1: Ancillary data sets for use in retrieval of soil moisture from AMSR data.

Data Set	Original Resolution	Source	Comments
Surface Topography	30 arc-sec	USGS/EDC	GTOPO30 Global DEM
Soil Texture	0.08° x 0.08°	Global GRASS1	Based on Zobler, 1986
Land Cover	1 km	USGS/EDC	
NDVI	1 km x 1 km	AVHRR, MODIS	
Surface Temperature	2° x 2°	GSFC/DAO, NCEP, ECMWF	

the polarization index methods, table look-up or iterative schemes can be used. These may be based on a simple forward model such as Equation (1) or on empirical data. Alternatively, a nonlinear regression equation can be developed.

As an alternative to using ancillary data for the surface temperature corrections, or using brightness temperature indices to normalize the surface temperature effects, higher frequency AMSR channels can be used to estimate and correct for surface temperature variability. At higher frequencies, and vertical polarization, the brightness temperature is less sensitive to soil moisture and vegetation, and more sensitive to surface temperature [14]–[16]. Thus, the 6.9, 10.7, and 18 GHz channels at both polarizations (six channels of information) can be used to estimate surface temperature, vegetation moisture content, and soil moisture independently. An iterative retrieval scheme based on the model of Equation (1) can be used to implement this approach.

The AMSR data will require screening for land surface type prior to implementing the soil moisture retrieval algorithms described above. Land cover databases and classification algorithms will be used to identify locations of dense vegetation, open water, snow cover, variable topography, and other adverse surface conditions. For these purposes, it is advantageous to pre-process the ancillary data sets and brightness temperature data to the same grid. The data sets, classification algorithms, and soil moisture retrieval algorithms, can then be managed similar to a conventional geographic information system.

5. ALGORITHM TESTS

The soil moisture retrieval approaches discussed above have been tested to varying degrees using theoretical simulations, experimental data from ground-based and airborne campaigns, and satellite data. Descriptions of this research can be found in the literature [4], [9], [13]. Realistic tests using satellite data are hard to perform. The best satellite data for simulating AMSR C- and X-band measurements are the Nimbus-7 SMMR data covering the time period 1978–1987. Unfortunately, there are no suitable in-situ measurements available during this period for validating soil moisture retrievals using the

SMMR data. However, an intercomparison test of the different approaches was carried out recently using a data set provided by NASDA of in-situ soil moisture measurements from sites in the former Soviet Union. Soil moisture data from 79 stations, sampled every 10 days, were compared with corresponding soil moisture values retrieved from SMMR data. The in-situ data were measured at point locations, averaged over the top 10 cm of soil. No site data on vegetation cover, topography, or surface temperature were available. The SMMR measurements are footprint averages over an approximately 120-km horizontal scale and the top centimeter of the surface. The discrepancies between the in-situ and SMMR spatial sampling, and the lack of ancillary information on surface characteristics, adversely affect the quality of the intercomparisons. Figure 1 shows one example of the results obtained.

The results indicate some agreement between the satellite and in-situ observations, but there is significant scatter (rms of ~8% volumetric soil moisture, or 0.08 g cm^{-3}). All the algorithms tested performed more or less in this range, although tuning to specific sites yielded better results. The soil moisture accuracy to be expected from AMSR is approximately < 0.06 g cm^{-3} (in areas where the vegetation cover is less than ~1.5 kg m^{-2}), with better accuracy expected for lower vegetation cover and where the surface characteristics are well known. In view of these sampling and data quality issues the comparison results of Figure 1 are consistent with expectation. A major effort will be required to develop suitable validation data at different global locations to evaluate the quality of the AMSR soil moisture estimates.

6. FIELD EXPERIMENTS AND VALIDATION

Validation plans for the AMSR soil moisture products are currently under development. An initial version of the EOS-PM1 AMSR soil moisture validation plan is available at the web site http://eospso.gsfc.nasa.gov/validation/valpage.html. The validation plan proposes a combination of enhanced in-situ ground measurements at dedicated test sites, ground-based and airborne radiometer measurements, model output data, and intercomparisons with other spaceborne sensors. The dedicated test sites will require enhanced in-situ instrumentation to provide dense sampling over the spatial extent of a few AMSR footprints (~200 x 200 km). These sites need to be automated to provide continuous sampling at 6-hourly intervals, permitting interpretation of diurnal effects on the surface soil moisture. A primary validation site is the U.S. Southern Great Plains (SGP) region centered in Oklahoma. This site was the location of previous L-band soil moisture field experiments, and is the location of the L- and C-band field experiments to be conducted in July 1999 (SGP'99). The SGP'99 experiment plan is available at the web site http://hydrolab.arsusda.gov/sgp99/.

Validation of soil moisture over areas larger than the dedicated sites will be difficult since the only independent estimates of soil moisture at these scales are products derived from hydrometeorological models, computed from knowledge of surface land cover, soil and topographic characteristics, and budgets of energy and water at the Earth's surface. These models themselves have inherent errors that are not yet well understood. Studies using these model products will be pursued in collaboration with data assimilation groups and the operational forecast centers (e.g. NCEP, ECMWF). In addition, the in-situ data collection and modeling activities of international programs such as the GEWEX Coordinated Enhanced Observing Period (CEOP) experiments will be utilized to the extent possible.

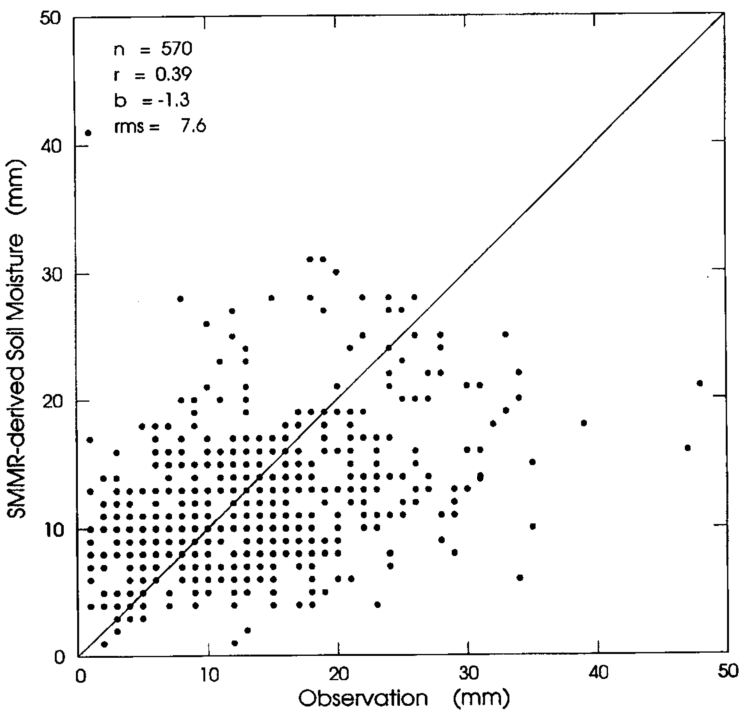

Figure 1. Comparison between soil moisture estimates from SMMR and in-situ observations. In-situ data are from sites over the former Soviet Union.

7. CONCLUSIONS

In this paper, some approaches currently under study for retrieving soil moisture from AMSR data have been described. The theory and experimental background for these approaches is well established. However, the complexity of natural terrain makes the retrieval of soil moisture a difficult problem. Continued experiments involving enhanced in-situ surface observations, airborne sensors, and satellite data are necessary for further improvement of the AMSR retrieval algorithms and for validation of the derived soil moisture products after launch.

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